What Is Urban? Comparing a Satellite View with the Demographic and Health Surveys

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There is widespread awareness that the world is becoming increasingly urban, both in the share of population living in urban areas and in the geographical extent of those areas. Our understanding of these trends is limited, however, by the lack of both a standard definition of an urban area (UN 2008) and agreed-upon spatial boundaries of urban areas (Balk 2009; Gamba and Herold 2009). This lack of a common framework makes cross-country comparisons and aggregations difficult: researchers may not know exactly what is captured by a seemingly simple dichotomous urban–rural variable. Illustrating this point, Utzinger and Keiser (2006), in their review of urban definitions used in 228 countries, found definitions constructed using ten distinct sets of criteria. Definitions are most commonly based on population size, economic activity, administrative function, or some combination of these. But differences exist even within definitional categories. For instance, although many countries define urban areas on the basis of population size or densities, the thresholds vary.[1]

Moreover, a standard dichotomous urban definition may not be satisfactory if it fails to adequately describe and categorize contemporary human settlements. Many of today's rural settlements have acquired characteristics that in the past were associated mainly with urban settlements (e.g., increased access to services and amenities associated with city living); and new types of settlements have emerged, such as conurbations, the large urban areas resulting from the merging of neighboring towns across interstitial rural areas (Wratten 1995; Hugo, Champion, and Lattes 2003; World Bank 2009). Consequently, the recent *World Development Report* focused on economic geography illustrates urbanness as a continuum rather than a dichotomy (World Bank 2009, Figure 1.1). Because data users have many different analytical objectives (ecological, political, social, economic, and cultural), a classification rule based on a single dimension, even if the definition represents a continuum, will not satisfy all users. One alternative is a multidimensional framework that incorporates several features to characterize human settlements[2] (Champion and Hugo 2004).

This article seeks to explain differences in the definition of "urban" between a satellite-based dataset, the Global Rural–Urban Mapping Project (GRUMP), and a survey-based dataset, the Demographic and Health Surveys (DHS).[3] We do not use these data to create a new definition of urban. Instead, by comparing these two definitions of urbanness, we hope to better understand what is meant by urban in these widely used data sources as well as in the larger data user communities that each dataset serves. We cross-validate the survey- and satellite-derived datasets by analyzing the distribution and household characteristics of DHS clusters falling within and outside of GRUMP urban extents. The goal of this cross-validation is to answer the following questions: 1) Do the GRUMP urban extents adequately capture places that report being electrified in the DHS? 2) How well do DHS urban–rural classifications, which are based on national statistical offices' definitions of urban, correspond to GRUMP extents? 3) Are there systematic differences in household or geographic characteristics that account for discrepancies between the GRUMP and DHS definitions of urban? If so, what are the implications of these discrepancies?

Our analysis reveals that GRUMP urban extents identify the majority of highly electrified localities, although the measurement is imperfect. Further, we find only moderate agreement between the urban classifications used by GRUMP and DHS: while GRUMP urban extents detect most of the locations defined as urban by DHS, they also identify as urban many locations identified as rural by DHS. Upon closer inspection, these locations tend to be peri-urban and possess many functional urban characteristics. As a result, we argue that when used in combination, GRUMP urban extents and DHS urban classification can produce a more refined definition of urbanness than is available from either dataset alone.

Sources of data on urbanness

Demographers are in large part responsible for the development of major survey programs such as the DHS, which collect household-level data systematically in many developing countries. Spatial coordinates are now routinely collected, allowing these data to be used in a spatial context. This allows data users to add environmental and contextual information—for example, on climate characteristics or on distances between survey locations and cities (e.g., Balk et al. 2004; Kudamatsu, Persson, and Stromberg 2010; Boco 2010)—that is not otherwise collected by the survey. In the present analysis, the contextual data are an independent measure of urban areas. Before proceeding, we briefly describe the DHS and GRUMP.

DHS

The Demographic and Health Surveys collect nationally representative data on household and individual characteristics throughout the developing world. As of 2009, the DHS program had collected spatial data indicating the location of the survey cluster (from which households are drawn) in 67 surveys across 36 countries (MEASURE DHS website n.d.). For the surveys with spatial information, the DHS provides geographic coordinates (geocodes) for each sampling cluster, which comprises approximately 15–30 households. Clusters are identified as rural or urban according to each country's national statistical office (NSO) classification scheme. We then spatially link geo-referenced DHS data to GRUMP data, which estimate the spatial extent of urban areas based on satellite imagery of nighttime lights (CIESIN et al. 2004). Whereas the DHS uses the respective NSO's urban–rural classification, which varies from country to country, GRUMP's definition is based on a systematic and globally consistent measure. The DHS collects information from each household on whether it is electrified; this measure is based on respondents' reports rather than interviewers' observations. Household electrification and urban–rural classification are the primary characteristics of interest for this analysis. Table 1 categorizes the DHS and GRUMP datasets.

GRUMP

The GRUMP urban extent dataset spatially delineates the boundary or "footprint" of urban areas, along with information such as place name, population, and area.[4] To detect urban extents, GRUMP primarily uses the 1994–95 stable city-lights dataset from the National Oceanic and Atmospheric Administration's nighttime lights satellite data, which measure permanent light, primar-

TABLE 1 Comparison of data sources and definitions in DHS and GRUMP datasets

	DHS	GRUMP
Urban definition	NSO-supplied urban definition; differs by country	Named settlement locations of places with more than 5,000 persons, but dependent on country-specific data availability.[a]
Electrification	Survey question "Do you have access to electricity?"	1994–95 stable city-lights dataset(detect electrification and permanent fires)
Amenities	Survey questions on: Access to safe water, Access to sanitation, Number of rooms, Material of flooring	None

[a]To give two examples, in China places with 20,000 persons were used as a lower bound; in Nigeria, data on the population of cities and towns were not available for places with a population of less than 50,000.

ily electrification (Elvidge et al. 1997). Details of database construction can be found elsewhere (Balk et al. 2005; Balk 2009), but salient elements are reviewed here. Names (and population estimates) associated with human settlements are compiled from NSOs and external sources. Such information is typically made available from NSOs without geographic identifiers, so geographic coordinates, which allow us to render settlements as geocoded points, are collected from gazetteers and the like. The population of a GRUMP extent is, as a first pass, calculated by summing the populations of settlement points located within the extent and then cross-validated by ensuring the population totals do not exceed the population values for the administrative areas which each extent overlaps. Because population data for administrative units and settlement locations often vary considerably, the final assignment of a population value to a GRUMP extent is an iterative process.[5]

Some known small cities or towns are not detected in the nighttime lights satellite data; in these cases, two steps were taken to account for this deficit: (1) Digital Chart of the World (DCW) polygons, known to be out-of-date, are used to detect places for which there are no lights. (2) Where there exist settlement points but neither lights nor a DCW polygon, urban extents were estimated as fictive lights in the shape of a circle, the size of which is predicted from a country- or region-specific regression of urban extent size on population. In our analysis, we distinguish these imputed extents ("circles") from the light-derived and DCW-derived extents. GRUMP systematically captures locations with populations greater than 5,000 except in China, where it captures locations greater than 20,000 (Balk et al. 2005).

The time-series lights data (1992/3–2009) (Baugh et al. 2010) have considerably more blooming or "overglow"—that is, a spatial over-extent of lighted area—than the stable city lights (Small, Pozzi, and Elvidge 2005), which themselves are deemed to produce larger urban "footprints" than other satellite-based estimates of urban areas (Potere et al. 2009). While the nighttime lights time series offer much promise (Zhang and Seto 2011),[6] the issue of "blooming" has not been addressed, rendering them impractical to use at the present time. The GRUMP version of the nighttime lights data has two added features found in no other urban extent data base: (1) it creates fictive extents for poorly electrified but known locations, primarily in Africa, as described above; and (2) each light (or fictive light) is cross-validated by a population settlement with name and population size. These factors make GRUMP a uniquely qualified data source for comparison with DHS data.

Using a definition so closely associated with electricity raises the question of whether electrification is a prerequisite for urban functionality, and similarly whether bringing electricity to rural areas will "urbanize" them. We argue that settlements do not have to be electrified to be urban, but in the developing world and especially in sub-Saharan Africa, "electricity is largely confined to the energy-intensive sub-sector of commercial and industrial enterprises as well as high-income households" (Karekezi 2002, p. 918); that is, electrification is concentrated in urban areas and, conversely, absent from rural areas (Doll and Pachauri 2010). A recent study found that nighttime lights are also correlated with economic activity even in Africa (Henderson, Storeygard, and Well 2012). Furthermore, in industrialized countries, while rural dwellers have access to electricity, they are not classified as urban by nighttime lights. This is because satellite observations of nighttime lights capture the contiguity and density of electrification infrastructure and related services, and rural dwellers in many industrialized countries tend to live far from one another. Consequently, unless extensive electrification projects were located in a dense or large area, the nighttime lights data will likely not detect them.

Other urban maps

Most global urban maps base their definitions on measures of land use, such as impervious surface area or contiguity of built environment in contrast to vegetative areas (Schneider, Friedl, and Potere 2009; Herold and Gamba 2009). In contrast, GRUMP is not a measure of land use; rather, it relies primarily on contiguous electrification, which, we argue, should correspond to high levels of access to services, a construct of urbanness that is used widely in the demographic community (Champion and Hugo 2004).[7] Nevertheless, in a recent study, Small et al. (2011) showed that these global urban datasets are alike in some important ways; and with respect to their measurements of urban areal extent, they all follow power laws, which is to say that they share a similar structure of rank-size rule (Zipf 1949).

The literature on validating the quality of global urban maps typically compares satellite-derived global urban maps to a high-resolution, remotely sensed standard at a country or city level (Tatem, Noor, and Hay 2005; Schneider, Friedl, and Potere 2009; Potere et al. 2009).[8] These studies found that most pixels classified as urban by the high-resolution maps fall within GRUMP urban extents, but a large number of pixels classified as rural do so as well. The comparisons in these studies are critical in evaluating differences among remote-sensing data and techniques, but the intended objective or use of the data determines which dataset is best (Small 2005; Small 2009).

It is also notable that most comparisons of satellite data products that detect urban areas omit the kind of cross-validation we undertake here: comparing satellite-based measures of urban areas with those from the ground. This article offers the first systematic analysis of this kind. We compare a global urban satellite-derived map, GRUMP, with geo-referenced household data, DHS, both of which measure a single construct, electrification, and both of which aim to measure urbanness.[9] This allows us to compare the global urban map to country-specific definitions and learn more about the characteristics of the localities categorized by the global map. Other global urban maps that are based on vegetation or impervious surfaces do not have an analogous measure in the household surveys with which to pair it. We establish a method that can be used subsequently to compare other global urban maps with DHS data to see how well, for instance, built area captures locations with high levels of services or electrification.

Data and method

We combine 20 DHS surveys conducted between 1990 and 2000 with GRUMP urban extent data to determine what the combination reveals that is not evident when only one source is used. The temporal restriction is imposed because GRUMP extents are based on 1994–95 imagery and cannot capture localities electrified after that time.[10] For countries with multiple DHS surveys, we use the survey closest to 1994–95. All but one (Bangladesh) of the 20 geocoded DHS surveys in this period are in Africa (see Appendix Table A.1), and of these, all but two (Chad and Egypt) are in sub-Saharan Africa. The restriction of our analysis to Africa and Bangladesh arises because the early DHS geocoding efforts were concentrated there.

A DHS survey cluster, the primary sampling unit for DHS, comprises a group of households. The geographic data (latitude and longitude) attributed to the clusters are presumed to be the geographic centroid of the group of households (Montana and Spencer 2001; Balk et al. 2004). In rural areas, clusters may contain households from more than one village and may represent a geographically large area; in contrast, urban clusters tend to represent geographically small areas (Balk et al. 2004). We compute cluster-level variables,[11] which can be thought of as neighborhood characteristics. The primary variables of interest are cluster electrification (calculated as the proportion of households in the cluster that have electricity) and urban–rural classification (which is constant within each cluster). Because we are interested in functional definitions of urbanness, we also examine indicators often used to measure poverty and urbanness, such as the proportion of households in the cluster with access to improved drinking water and toilet facilities (WHO/UNICEF JMP 2010), durable flooring, and adequate living area. With the exception of adequate living area, these indicators measure access to urban amenities.[12]

Access to improved water and sanitation is defined on the basis of guidelines from the WHO Joint Monitoring Program for Water Supply and Sanitation (WHO/UNICEF JMP website 2010). A household is coded as having access to improved drinking water if the water is piped into the dwelling or yard/plot; or if water is from a public tap/standpipe, tube well, well with a pump, borehole, protected well, protected spring, or rainwater. Bottled water is considered a protected source, although the WHO/UNICEF JMP website highlights some problems with this. Our definition of improved water, then, refers to the source and not necessarily the quality of the water, which may decline with urbanization if the infrastructure is inadequate. Improved sanitation includes flush toilets regardless of whether excreta go into a sewer or septic tank, and pit latrines that are ventilated or are covered with a slab. Durable flooring includes finished flooring such as cement, tiles, linoleum, and parquet, but not earth floors or wood planks (UN-Habitat 2006). Adequate living area is defined as no more than three people sleeping in the same room; many surveys, however, do not contain information on this last indicator.

Adjusted weights

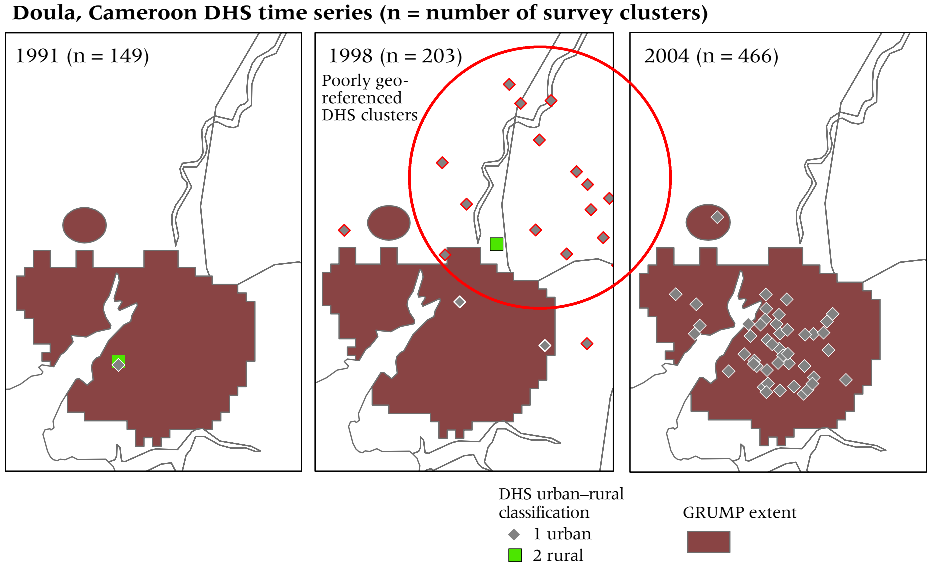
Our analysis pools together clusters from all 20 DHS surveys. We devise a weighting scheme for the clusters to take account of the large differences in country populations and sample sizes between surveys, as well as the fact that the number of clusters in each survey is not proportional to the country's population size (see Appendix Table A.1).When analyzing the clusters in a pooled sample, we adjust for these differences by rescaling the survey's sample weights to represent the 20 countries in proportion to their populations. We follow the method of Balk et al. (2004), calculating an expansion weight for each country, multiplying this weight by the original sample weight, and renormalizing so that weights average to 1.0 across the pooled sample. Our regression analysis uses weighted OLS[13] to obtain the correct standard errors (Winship and Radbill 1994).

Data quality

GRUMP has some known shortcomings. The main problem is that the 1994–95 stable city nighttime lights that underlie this dataset, while better than the other nighttime lights datasets, still exhibit some "overglow." Hence, the measured light extents are larger than urban extents measured in other ways, such as impervious surface measurements (Elvidge et al. 2004; Tatem, Noor, and Hay 2005; Potere and Schneider 2007). Furthermore, in less-developed regions, such as in Africa, GRUMP may fail to detect some small and poorly electrified urban areas, despite the imputation efforts described above (i.e., "circles").

The DHS geocoding procedures have been subject to errors, especially in the early stages of this effort in the 1990s. In Cameroon, for example, it appears that there are geocoded clusters that should be located within urban areas, but are not[14] (Figure 1 shows the example of Doula, Cameroon). We can detect this problem by comparing three years of DHS data and by overlaying GRUMP urban extents. Both comparisons reveal clues to inconsistencies over time and place in the geocoding. Without the spatial information from

FIGURE 1 GRUMP urban extents and DHS clusters in Doula, Cameroon in 1991, 1998, and 2004



NOTE: A large number of clusters classified as urban by the DHS in 1998 were located north of GRUMP urban extents, as seen in the middle panel. We used Google Maps to verify that the locations of these clusters do not appear to be in urban areas.
SOURCE: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

GRUMP, one might assume that the cluster locations for the 1991 and 1998 surveys represent different neighborhoods in Doula. However, clusters in the 2004 survey and the smaller 1991 survey fall mostly within the urban extent, suggesting that something is amiss with the coordinates for 1998.[15] In some countries, many clusters (sometimes both rural and urban) share the same point location (as in the 1991 panel of Figure 1). Chad's 1996–97 DHS, where 247 clusters share just 45 unique point locations, provides the most obvious example. Data collection shortcomings in the early rounds of the geocoding may be to blame. Another common problem results in some cluster points being located outside of the respective country's administrative boundaries. This arises from the lack of standard operational boundaries for use both when fielding surveys and when later disseminating the DHS data. An effort is underway to overcome this problem, and the DHS has instituted procedures to ensure that early problems have not been repeated in more recent survey rounds.[16]

Method

We spatially integrated the DHS data with GRUMP urban extent data using programming tools in ArcMap 9.3 and Python 2.5. Any DHS cluster point located within an urban extent or located less than 3 km from a boundary of the urban extent becomes associated with that urban extent. We assigned cluster points within a 3-km buffer to a GRUMP urban extent to make the treatment of the DHS cluster points consistent with the other datasets. The nighttime lights are accurate within 3 km[17] (Elvidge et al. 1997), thus the settlement point locations used in GRUMP were associated with the nearest light up to a distance of 3 km (Balk et al. 2005). In what follows, we describe these clusters as being within a GRUMP urban extent, regardless of whether the cluster falls within the extent itself or within 3 km of it. More than half of all DHS clusters were spatially matched with a GRUMP extent.

The following analysis consists primarily of simple statistics based on the integrated data, including spatial measurements, coupled with illustrative figures. We use OLS regression for more complex description. Each method is described in turn below.

Results

Do GRUMP urban extents capture electrified places?

In this section, we use DHS clusters to quantify GRUMP's ability to identify electrified localities. Specifically, we compare the distribution of cluster electrification (the proportion of a cluster's households with electricity) within and outside of GRUMP extents. We also analyze the likelihood that clusters with a certain proportion of electrified households are located inside a GRUMP extent.

On average, clusters located inside GRUMP urban extents are much more highly electrified than clusters outside these extents (see Table 2). Sixty-six percent of DHS clusters inside GRUMP extents have at least 75 percent of households electrified, compared with less than 8 percent of DHS clusters outside of GRUMP extents. Still, 733 clusters inside GRUMP extents—a little more than one tenth when weighted—are not electrified. Later in this section we examine whether the poorly electrified clusters were joined with GRUMP's "circles"—the imputed extents based on regression estimates rather than on direct nighttime lights—or whether these clusters represent poor neighborhoods within GRUMP extents. In other words, we seek to determine whether the fact that some within-city neighborhoods are not electrified is a socioeconomic feature of cities, or a disagreement of the measurement between GRUMP and DHS. Likewise, we seek to understand why 51 fully electrified DHS clusters were not in GRUMP extents.

What is the likelihood that clusters with a minimum proportion of electrified households are captured by—that is, spatially matched to—a GRUMP extent? Table 2 shows that GRUMP extents contain the overwhelming majority of electrified clusters, especially highly electrified ones—92 percent of clusters with more than 99 percent of households electrified. But as the proportion of electrified households decreases, so does the probability that GRUMP extents capture these clusters. Only 16 percent of the non-electrified

TABLE 2 Distribution of DHS cluster-level electrification by GRUMP urban classification

Percent of households electrified in each cluster	Clusters within GRUMP extents (urban clusters)		Clusters outside of GRUMP extents (rural clusters)		Percent of clusters captured by GRUMP extents
	Number	Percent[c]	Number	Percent[c]	
100	760	40.7	51	3.8	92.0
75–99	732	25.0	48	4.1	86.1
50–74	399	9.1	49	3.2	75.4
25–49	334	6.8	88	5.6	56.6
1–24	398	6.2	349	14.6	31.1
0	733	12.1	2,172	68.8	15.9
Missing[a]	187	—	111	—	
Total[b]	3,356	100	2,757	100	—
Mean electrification (percent)	72.1		12.9		

[a]Nigeria DHS clusters do not have information on cluster electrification.
[b]Total excludes clusters with missing electrification information.
[c]Based on sample weights.
DATA SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

clusters were included in GRUMP extents. The same pattern was found with the unweighted data.

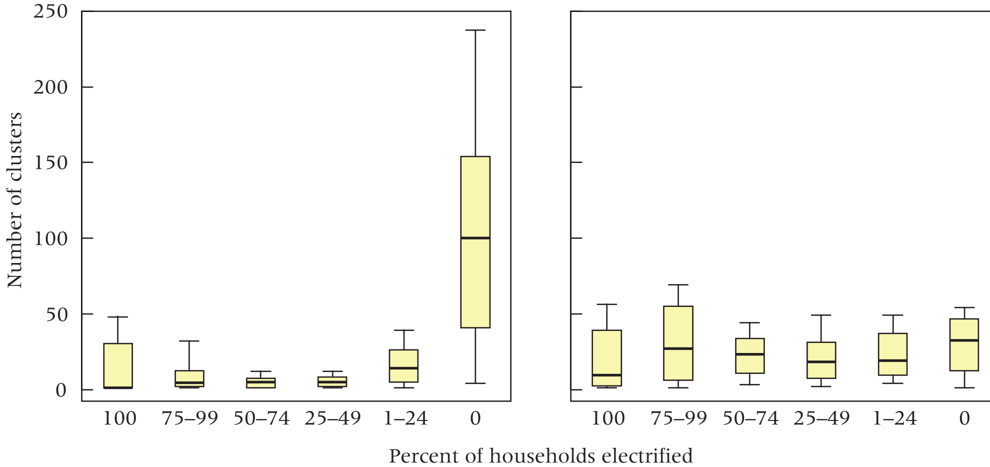
Figure 2 shows box plots of the frequency distribution of DHS clusters in our pooled sample, within and outside of GRUMP extents, by electrification category. Panel A (unweighted) indicates that most clusters outside of GRUMP urban extents are not electrified; there are very few well-electrified clusters outside of GRUMP extents, with the exception of Egypt, which accounts for 48 of 51 fully electrified clusters. Panel B (unweighted) shows that even within GRUMP extents there is wide variation in cluster electrification. Panel C (weighted) shows that GRUMP extents tend to capture the highly electrified clusters; as electrification declines, a cluster is less likely to fall within a GRUMP extent.

Electrification by GRUMP source. As mentioned above, while GRUMP extents are primarily based on nighttime lights ("lights"), there are two other sources of urban footprints: imputed "circles" and DCW footprints. Lights represent the majority of GRUMP extents within which DHS clusters fall. Although the majority of the clusters within lights are highly electrified (the mean proportion of electrified households is 78.9 percent), there are still a substantial number (240) of poorly electrified clusters within lights. On average, confirming our expectation, clusters that fall within circles and DCW footprints are poorly electrified. More than half of the non-electrified clusters captured by GRUMP fall within circles, which were not based on nighttime lights imagery (see Table 3).

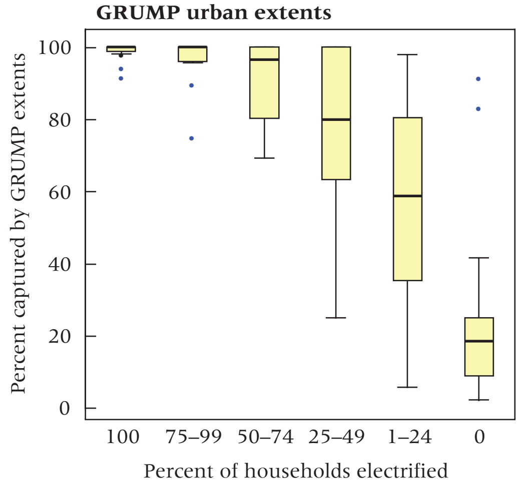
FIGURE 2 Country-level box plots showing the distribution of DHS clusters by cluster-level electrification and GRUMP urban extents

Panel A
Outside of GRUMP urban extents[a]

Panel B
Within GRUMP urban extents[a]



Panel C
Likelihood that a cluster with given electrification level is captured by GRUMP urban extents



[a]Excludes outliers.
NOTE: The lower and upper bounds of the box represent the lower and upper quartiles of the distribution of the number of clusters in each electrification category. The midline in the box represents the median and the whiskers represent the minimum and maximum of the distribution.
SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

Table 3 further shows that highly electrified clusters are more likely than poorly electrified ones to be located in larger and more populous GRUMP extents. The mean area of GRUMP extents with non-electrified clusters is

TABLE 3 Distribution of DHS cluster-level electrification by GRUMP extent source, geographic area, and population size (unweighted unless noted)

	Source of GRUMP extents			All GRUMP extents	
Percent of households electrified in each cluster	Night-time lights (no.)	Imputed "circles" (no.)	DCW settle-ments (no.)	Average size of GRUMP extents (km²)	Average population of GRUMP extents, 1995 (thousands)
100	754	2	4	2,685	5,098
75–99	705	26	1	3,191	4,218
50–74	354	41	4	1,058	1,526
25–49	279	51	4	277	544
1–24	277	108	13	158	352
0	240	425	68	65	94
Summary	**Mean cluster-electrification levels (percent)**			**Size**	**Population**
Unweighted	66	10	7	1,436	2,357
Weighted	79	23	22	2,016	4,220

NOTES: Nigeria does not have information on cluster electrification and is excluded from this analysis.
DATA SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN)

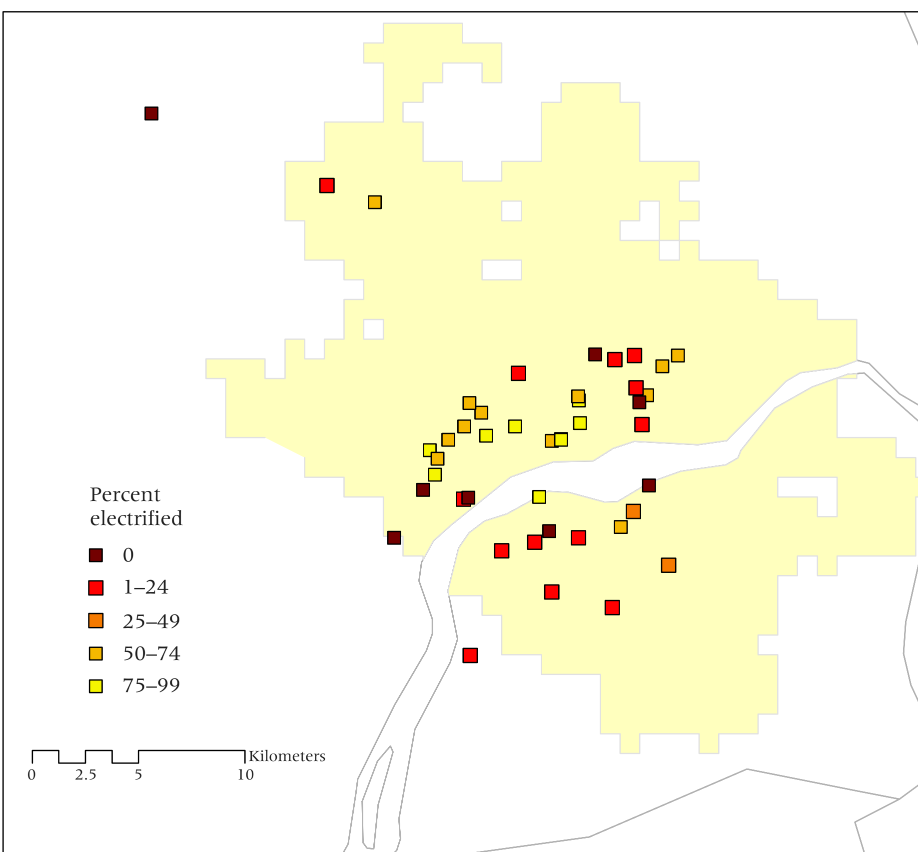
65 square kilometers; the mean with fully electrified clusters is 2,685 square kilometers. The mean 1995 population of urban extents within which fully electrified clusters are located is nearly 5.1 million persons; the mean population of GRUMP extents within which non-electrified clusters are located is less than 100,000. (Applying the weights increases the mean electrification, size, and population of GRUMP extents.)

It is no surprise that GRUMP extents more accurately identify clusters in large electrified clusters than in small poorly electrified ones. It is also no surprise that the majority of the poorly electrified smaller localities that were captured fell within circles or DCW-based footprints: these footprints were specifically intended to capture smaller localities. This brings to mind two questions. Are the poorly electrified localities that fall within circles or DCW footprints considered urban by some other measure (such as the NSO's urban classification used by the DHS)? Should GRUMP expend additional effort to better capture these smaller, poorly lighted localities? We return to these questions below.

Can poverty explain poorly electrified clusters found within GRUMP extents? GRUMP extents, by definition, indicate localities that are electrified, but we cannot assume that there is a consistent degree of electrification throughout a given urban extent. Cities are internally heterogeneous: they contain under-serviced, poor, and slum neighborhoods, which often lack electricity, as well as wealthy neighborhoods with a full range of services (National Research Council 2003). We can test the hypothesis that poorly electrified clusters captured by GRUMP extents are located in under-serviced neighborhoods (see Figure 3). We recognize that not all slum dwellers are poor, that the poor do not exclusively live in slums, and that the poor may live in well-serviced areas (Montgomery and Hewett 2005). Nevertheless, we use the proportion of households without access to improved water and sanitation, durable flooring, and adequate living area as a proxy for poverty. These variables account for many of the variables used by UN-Habitat to define slums (WHO/UNICEF JMP 2010).

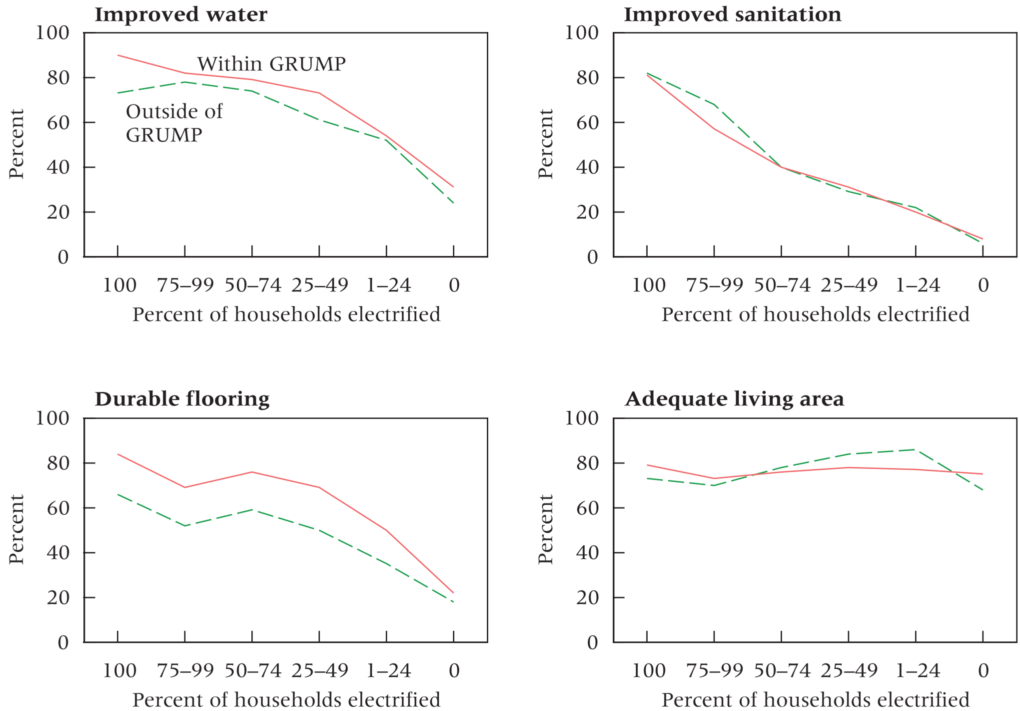
Figure 4 shows that electrification is highly correlated with other household amenities regardless of location. In clusters with no electrified households, access to improved water and sanitation is lower and fewer homes have durable flooring as compared to clusters with a large proportion of electrified households. As the prevalence of electrification decreases, so does the prevalence of these other amenities. Access to improved sanitation shows

FIGURE 3 Variation in cluster-level electrification within GRUMP urban extent, Bamako, Mali



NOTE: No clusters are 100 percent electrified.
SOURCE: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

FIGURE 4 Mean level of household amenities by DHS cluster-level electrification within and outside of GRUMP urban extents



NOTE: Ouside of GRUMP indicates rural as defined by GRUMP.
SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

the strongest—and most linear—relationship with electrification. Adequate living area shows no relationship with electrification.

We next compare these household amenities for DHS clusters that fall within and outside of GRUMP urban extents. Non-electrified clusters within GRUMP urban extents have greater access to improved water, improved sanitation, and durable flooring than non-electrified clusters outside of GRUMP urban extents. Although statistically significant ($p < 0.001$), the magnitude of the differences is relatively small. With the exception of access to improved sanitation, highly electrified (greater than 75 percent) clusters within GRUMP urban extents are better off than highly electrified clusters outside of GRUMP urban extents in terms of household amenities. We find that sanitation varies considerably with the proportion of the cluster electrified. Clusters with low levels of electrification, regardless or whether they fall within or outside of GRUMP urban extents, are less likely to have improved sanitation.[18]

We use weighted OLS regression to determine whether the strong association remains between electrification and GRUMP urban extents when controlling for other household poverty proxies (improved water and sanitation,

TABLE 4 Weighted regression estimates predicting DHS cluster-level electrification: Pooled sample of 19 African countries and Bangladesh

	Coefficient	Standard error
Within GRUMP extents	0.286***	0.044
Percent of households with improved water	0.034#	0.019
Percent of households with improved sanitation	0.525***	0.038
Percent of households with durable flooring	0.219***	0.028
Percent of households with adequate living area	0.038	0.039
GRUMP*improved water	0.177***	0.031
GRUMP*improved sanitation	–0.329	0.038
GRUMP*durable flooring	0.068*	0.033
GRUMP*adequate living area	–0.163***	0.051
Constant	–0.040	0.049
R-squared	.828	
N	5,994	

significant at p<0.10; *significant at p<0.05; ***significant at p<0.001.
NOTE: Country dummies included in regression but not shown.

durable flooring, and adequate living area). We also control for interactions between being located in GRUMP extents and these indicators of household poverty. Finally, we include country-specific dummy variables. The results of the regression, shown in Table 4, confirm our descriptive statistics. Clusters that fall within GRUMP extents are significantly more electrified than those located outside. Clusters with no access to improved water, no access to improved sanitation, no durable flooring, and/or insufficient living area were significantly less electrified than clusters with access to these amenities. From the interaction terms, we find that the effect of improved water and durable flooring is even greater in urban areas. Improved sanitation, however, has a negative interaction: while access to sanitation is associated with higher levels of cluster electrification, this effect is reduced in urban areas, presumably because some urban dwellers live in poverty with limited access to this type of infrastructure, despite access to electricity. Similarly, the interaction of urban area with adequate living space—which does not vary with electrification—suggests that living area has a modest positive association with electrification in rural areas and a negative association in urban areas. Perhaps electrification is more likely in urban areas when housing is compact, such as in high-rise dwellings. This simple model captures much of the variation in cluster electrification ($R^2 = 0.83$). In sum, while poverty as proxied by lack of access to these key amenities helps explain why some poorly electrified clusters fall within GRUMP urban extents, these relationships—especially that of sanitation—are not always straightforward.[19]

Some critics of GRUMP argue that nighttime lights may be an inappropriate measure of urbanization in poor countries because they do not capture poorly lighted places. However, the evidence here suggests that

GRUMP detects clusters in which the majority of households are electrified. Furthermore, GRUMP is not based solely on nighttime lights: a large proportion of non-electrified clusters fell within the imputed "circles," suggesting that at least the 1994–95 stable city-lights data by themselves are insufficient to detect towns and other small cities in poor countries. Given that lights-based GRUMP extents measure electrified clusters, we now ask how they correspond to NSO classifications of urban.

Do GRUMP extents indicate urban areas?

GRUMP extents are often used to delineate urban areas (McGranahan, Balk, and Anderson 2007; Balk et al. 2004; Tatem, Noor, and Hay 2005). Here we analyze how well GRUMP extents capture localities classified as urban by DHS. We use the DHS urban–rural classification of the clusters within GRUMP extents to analyze whether GRUMP extents appear to overextend the urban areas that they are intended to proximally represent. In this analysis, it is important to remember that the DHS uses the definition of urban adopted by each country's NSO, and these definitions have for the most part undergone little modification in more than 50 years (Hugo, Champion, and Lattes 2003). Also, the conceptual basis from which these urban–rural dichotomies arose may or may not closely correspond to the concentrations of settlement and economic activity that the nighttime lights sensor proximally detects.

Table 5 shows that 94 percent of clusters classified as urban in the DHS are located within a GRUMP urban extent. Likewise, 69 percent of DHS rural clusters are outside of GRUMP extents. Borrowing the language of epidemiology, GRUMP extents are sensitive to the DHS urban classification: they detect the majority of DHS urban clusters; but they are not very specific: the extents also pick up a large portion of DHS rural clusters. Overall map accuracy, a measure of agreement, using DHS as the standard, is 79 percent.[20] When we adjust for the probability that some agreement occurs by chance (using Cohen's Kappa), the overall agreement falls to 59 percent. According to Landis and Koch (1977),

TABLE 5 Map agreement measures: Validating GRUMP extents based on DHS urban–rural classification

	DHS classification	
	Urban	**Rural**
Within GRUMP extents	2,339	1,204
Outside of GRUMP extents	137	2,731
Sensitivity = Percent of urban clusters captured by GRUMP	94.5	
Specificity = Percent of rural clusters not captured by GRUMP	69.4	
Probability that a cluster falling within GRUMP was urban (%)	66.0	
Probability that a cluster falling outside of GRUMP was rural (%)	95.2	

DATA SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

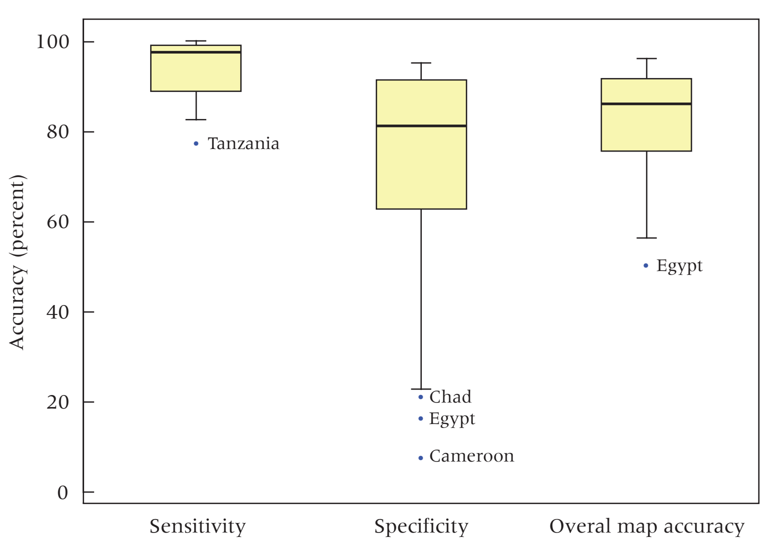
a Kappa of 59 percent indicates moderate agreement; this is expected since the two data sources rely on different but correlated urban definitions.

Of the DHS clusters that fell within GRUMP extents, 66 percent were classified by the DHS as urban. Therefore, 34 percent (n = 1,204) were clusters classified as rural by DHS but identified by GRUMP as urban. Similarly, of all the clusters identified as rural by GRUMP (i.e., those that do not fall in an urban extent), 5 percent (n = 137) were classified as urban by the DHS.

Figure 5 illustrates the results of the country-level map agreement measures. This figure shows three measures of accuracy at the country level: (a) sensitivity (or producer's accuracy) is the probability that a given cluster classified as urban by DHS will be classified as urban by GRUMP; (b) specificity (or user's accuracy) is the probability that a particular cluster located within a GRUMP extent is in fact urban according to the DHS; and (c) overall map accuracy. Accuracy statistics approach 100 when the DHS urban definition agrees with the GRUMP urban definition. At the national level, GRUMP is generally sensitive but has lower specificity, especially in Chad, Egypt, and Cameroon.

Six percent of the DHS urban clusters were not detected by GRUMP extents. Because GRUMP is primarily based on nighttime lights, a likely explanation for the exclusion of DHS urban clusters from GRUMP urban extents is limited electrification. Of the 137 urban clusters found outside of GRUMP extents, electrification information was available for 120 clusters. (Nigeria had no electrification information and is omitted from this analysis.) Of these urban clusters, 79 percent (95) were clusters where less than 50 percent of

FIGURE 5 Country-level box plots of three measures of agreement for GRUMP using DHS urban definitions



NOTE: Outliers are labeled.
SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN).

households were electrified; the electrification of these urban clusters may have been too limited to be captured by the nighttime lights. (This is likely the case in Tanzania: the 22 DHS urban clusters not captured by GRUMP urban extents had a mean electrification of 5.6 percent.) The remaining 21 percent (25) were well-lighted (more than 50 percent electrified), but they may have been too small to be captured by GRUMP. We confirmed this hypothesis by examining these locations in the satellite view of Google Maps.[21] All but one of these clusters are located in small towns of less than two square kilometers (as measured by scale on Google Earth).[22]

In addition to being significantly less electrified or small in size, we show in Table 6 that these DHS urban clusters not detected by GRUMP extents also have less access to improved water and sanitation, and are less likely to have durable flooring compared to clusters classified as rural by the DHS but included in the GRUMP extents. These clusters were much worse off than the clusters that were classified as urban by both GRUMP and DHS. In Table 6, by combining GRUMP and DHS urban classification systems into a continuum, we see clear patterns of all poverty-proxy indicators with respect to urbanness.

More than 30 percent of the rural clusters fell within GRUMP extents. What accounts for this low specificity? A large number (1,204) of DHS rural clusters are located within GRUMP urban extents. Possible explanations for the low specificity include suboptimal geo-referencing, rural electrification, proximity to an urban area, and outmoded or meaningless country-specific urban–rural classifications.

As we mentioned above, rural clusters in some countries are assigned the same coordinates as urban clusters; 230 rural DHS clusters with coordinates identical to urban clusters are captured by GRUMP urban extents. The majority of these poorly geo-referenced clusters are in Chad, Central African Republic, and Cameroon, which helps explain GRUMP's poor specificity in these countries.

TABLE 6 Mean percent of households with access to electricity, improved sanitation and water, durable flooring, and adequate living area by an urban continuum that combines DHS and GRUMP urban classification systems (weighted)

Urban continuum (from least to most likely urban)	Electrification[b]	Improved sanitation	Improved water	Durable flooring	Adequate living area
Rural, not in GRUMP extents	12	16	46	13	71
Urban, not in GRUMP extents	28	16	52	31	72
Rural, in GRUMP extents	59	47	67	32	72
Rural, in GRUMP extents[a]	61	49	68	33	72
Urban, in GRUMP extents	82	68	91	79	82

[a]Excludes the 230 DHS rural clusters with coordinates also identified by the DHS as urban.
[b]Omits Nigeria, which has no data on electricity.
DATA SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN)

High levels of electrification and therefore high levels of other household amenities might also account for the inclusion of these DHS rural clusters within GRUMP extents. The data suggest that rural DHS clusters included in GRUMP extents have significantly more urban characteristics than urban DHS clusters not captured by GRUMP. These rural clusters captured by GRUMP are not as electrified as urban DHS clusters captured by GRUMP. The relationship is stronger after removing the 230 poorly referenced DHS rural clusters (Table 6): the remaining subset of rural clusters found within GRUMP extents have slightly more urban characteristics across the board.

Clusters in which DHS and GRUMP disagree on urban status could primarily be peri-urban neighborhoods, located on the edges of urban areas. To test this hypothesis, we calculate the average distance from the edge of a GRUMP extent to the DHS clusters located within that GRUMP extent. Table 7 shows that DHS clusters classified as rural were closer to the edge of GRUMP extents, on average, than clusters classified as urban, with mean distances

TABLE 7 Among DHS clusters within GRUMP urban extents, mean distance to GRUMP extent edge and mean cluster-level electrification by DHS urban classification

	Distance to GRUMP edge (km)		Mean electrification (percent)	
Country and year	Urban	Rural	Urban	Rural
Bangladesh 1999–2000	2.28	1.45	76	36
Benin 1996	1.64	1.87	21	11
Burkina Faso 1992–93	2.88	2.88	18	0
Cameroon 1991	2.36	2.34	54	10
Central African Republic 1994–95	2.51	2.45	2	0
Chad 1996–97	2.07	2.07	2	0
Côte d'Ivoire 1994	1.71	1.18	59	19
Egypt 1995–96	2.69	1.78	99	95
Ethiopia 1999	1.99	1.26	78	4
Ghana 1993–94	2.11	1.65	66	12
Guinea 1999	1.83	0.64	47	13
Kenya 1998	2.90	1.54	51	11
Madagascar 1997	2.72	2.42	36	15
Mali 1995–96	1.55	1.80	19	0
Niger 1998	1.47	1.32	26	0
Nigeria 1990	3.55	2.87	—	—
Senegal 1997	1.98	1.49	59	23
Tanzania 1996	1.76	1.47	63	7
Togo 1998	1.61	1.40	25	6
Zimbabwe 1999	6.89	0.93	93	39

NOTE: Data on electricity missing for Nigeria.
DATA SOURCES: Demographic and Health Surveys; Global Rural–Urban Mapping Project (CIESIN)

of 1.86 km and 2.30 km, respectively. This supports the argument that rural clusters captured by GRUMP tend to be peri-urban.

While Table 6 is helpful in understanding mismatches between these different datasets and measures, it also demonstrates the potential for combining data sources in such a way that a continuum of urbanness can be articulated. This is not possible when either data source is used by itself.

Discussion and conclusion

This article has sought to explain differences in the conceptualization and measurement of urban, by comparing a major satellite-based dataset and a major survey-based dataset, GRUMP and DHS, respectively. Remotely sensed data capture physical aspects of the environment, and by joining them with survey data we obtained additional information that cannot be captured remotely, such as on conditions correlated with poverty like household access to safe water and sanitation. We conclude by discussing what the comparison has revealed about each approach.

What is meant by urban in GRUMP?

Large, highly electrified localities are more likely to fall within GRUMP extents than poorly electrified or small localities. A significant proportion of poorly electrified DHS clusters fall within GRUMP extents, but these extents were more likely to be imputed urban areas. Many poorly electrified clusters also fall within GRUMP urban extents, which we argue is a result of the heterogeneity of urban areas. With additional DHS-derived information on the household characteristics of these clusters, it is possible to place these poorly electrified clusters in their urban contexts.

Our results are in line with other studies which have found that GRUMP has high urban sensitivity (almost all locations considered urban by other data sources fall within GRUMP urban extents), but lower specificity (many locations considered rural also fall within GRUMP extents) (Tatem, Noor, and Hay 2005; Potere et al. 2009; Schneider, Friedl, and Potere 2009). We contend that GRUMP's low specificity is a consequence of its ability to capture peri-urban areas, which possess many urban characteristics.

What is meant by urban in DHS?

DHS urban classifications are based on each country's national statistical office's definition of urban. It is not surprising, therefore, that the distribution of urban characteristics (especially electrification and access to improved sanitation) within localities classified as urban is heterogeneous. As we showed in Table 6, there is greater homogeneity in amenities, for example, between localities captured by GRUMP extents (especially light extents) than in localities considered urban by the DHS. This means that in studies based on DHS datasets, the "urban" effect may be diluted; this is especially problematic for studies focused on rural–urban differences. For instance, Günther and Harttgen (2012) analyzed differences in child mortality between rural and urban populations in sub-Saharan Africa. The ratio of rural to urban mortality varied widely across countries, which is not surprising since the definition of urban varied by country. The results of our analysis may help explain some of this variation. The rural–urban ratios for child mortality were relatively low in Chad and Egypt because many clusters labeled as rural have many characteristics associated with urban extents; likewise the ratio for Tanzania was likely low because many urban clusters have very low levels of electrification and other amenities.

Limitations and future research

When survey data are more recent than nighttime lights measurement by five or more years, we find lower correspondence between the cluster's urban classification and GRUMP. This implies that later DHS surveys may be used to detect the emergence of new settlements and to quantify urban spatial growth in future nighttime lights or other satellite data series.

One consequence of this research is that users of DHS datasets can now use GRUMP urban extents—which are based on a global, systematic definition—as a measure of urban, instead of relying on country-specific definitions. Another benefit is that DHS data users now have information on city size in terms of both population and physical extent, information that until now has been notably absent from the surveys (and otherwise hard to create with existing information) (National Research Council 2003). The dataset created for this analysis can also be used to analyze intra-city variation in access to electricity, improved water and sanitation, durable flooring, and adequate living area or other indicators (such as education) that can be derived from the DHS.

Of note to data providers and other data users, the data quality issues encountered with the DHS raise concerns. While there appear to be fewer errors in the more recent surveys, uncritical use of early rounds of DHS geocodes may lead to flawed inferences. We caution users particularly with regard to DHS surveys from Chad, Cameroon, and Central African Republic. The DHS does not cross-validate the geocoded clusters with GRUMP; we would recommend that this be done.

Our analysis is limited by the temporal resolution of the GRUMP dataset. The number and diversity of countries with DHS surveys have increased over time. A more recent version of GRUMP would have allowed us to include many more countries in Latin America and Asia. Therefore, GRUMP should be updated. A critical vetting of whether the nighttime lights time series is a reliable indicator of urban change is needed.

With this groundwork laid, in future research we and others can critically evaluate population density as a marker for urban, since density thresholds are often used to define urban areas. Future work will also include comparing GRUMP and DHS datasets with an agglomeration index that is more closely tied to the economic definition of an urban area (World Bank 2009; Uchida and Nelson 2010). The agglomeration index is based on population size, population density, and travel time, which will provide a benchmark against which both GRUMP and DHS can be compared. Finally, comparing DHS to land-use-based urban datasets is also warranted. Comparing GRUMP and DHS views of urbanness has been revealing, and we anticipate learning from other comparisons as well. In the present comparison of GRUMP and DHS urban classifications, the agreement and discrepancies were informative, and in particular they permitted combining these datasets in a way that allowed a measurement of urban that is closer to a rural–urban continuum rather than the conventional dichotomy (Woods 2003).

The concepts that define urbanness are varied, and likely they will remain so. This variation and the likelihood of change over time make it imperative that we continue periodically to evaluate how to measure urban constructs as new data and methods become available.

APPENDIX TABLE A.1 List of DHS surveys included in the analysis, number of clusters in each survey, and estimated population of the country at the time of the survey

Country and year	Number of clusters	Population ('000) at time of survey
Bangladesh 1999–2000	341	135,466
Benin 1996	200	5,820
Burkina Faso 1992–93	230	9,087
Cameroon 1991	149	12,230
Central African Rep. 1994–95	231	3,506
Chad 1996–97	247	7,157
Côte d'Ivoire 1994	246	14,380
Egypt 1995–96	934	59,352
Ethiopia 1999	539	62,279
Ghana 1993–94	400	17,054
Guinea 1999	293	8,154
Kenya 1998	271	29,123
Madagascar 1997	269	14,377
Mali 1995–96	300	9,426
Niger 1998	268	10,196
Nigeria 1990	298	96,604
Senegal 1997	320	9,845
Tanzania 1996	357	30,392
Togo 1998	288	4,457
Zimbabwe 1999	230	11,733

SOURCES: Demographic and Health Surveys; US Census Bureau International Database

APPENDIX TABLE A.2 Formulas used for contingency table and map agreement measures

	DHS urban classification	
	Urban	Rural
GRUMP classification		
Urban	a	b
Rural	c	d
Sensitivity	a / (a + c)	
Specificity	d/ (d + b)	
Overall map accuracy	(a + d) / n	
Cohen's Kappa	$\dfrac{\left(\dfrac{a+d}{n}\right) - \dfrac{(a+b)(a+c) + (c+d)(d+b)}{n^2}}{1 - \dfrac{(a+b)(a+c) + (c+d)(d+b)}{n^2}}$	
Probability that a cluster falling within GRUMP was urban	a/ (a + b)	
Probability that a cluster falling outside of GRUMP was rural	d/(d + c)	

Notes

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1 As perhaps they should. For example, a village of 20,000 persons in India might not be considered urban while a town of this size in a more industrialized country would.

2 An example is the agglomeration index in the 2009 *World Development Report*. To be classified as urban a location must have a population above 50,000; a minimum population density of 150 people per square kilometer; and be within 60 minutes of the nearest large city (World Bank 2009). In this example the three dimensions are combined into a single index; alternatively, one could create Grade of Membership profiles, which retain information on the different dimensions (Guedes, Costa, and Brondizio 2009).

3 In essence, these two datasets represent, respectively, a satellite view of areas deemed to be urban because they have permanent light at night, and a collection of definitions used by national statistical offices (NSO). As we describe below, GRUMP is not the only satellite view of urban areas, but it is the only one that couples areas that are probably urban with settlement names (and population estimates); similarly, no such compendium of NSO definitions exists in a spatial framework apart from the one we have assembled here. We refer to these data sets below as GRUMP and DHS, but in fact they represent the larger structures upon which each of these collections is built.

4 This additional information, particularly place name and also population, is valuable in cross-validation. No other urban extent data apart from GRUMP (such as those reviewed by Potere et al. 2009 and Schneider, Friedl, and Potere 2009) contain this information.

5 This is a simplification of the rules according to which population values are assigned to GRUMP extents. GRUMP was created to refine the spatial delineation of urban places within coarse administrative areas. In addition to using population values, upper and lower values of population density were used

to redistribute population into the GRUMP extent (for details see Balk et al. 2005).

6 Unlike the GRUMP urban extents, which are based on a the 1994–95 stable city-lights data, the nighttime lights time-series data represent a continuum of urbanness (urban definition based on economic activity and population density) based on the brightness of the lights. The time-series lights also "bloom" more than the stable city lights, making that correction even more important before being used.

7 Furthermore, the transformation of the nighttime lights data into GRUMP has made the lights data easier to use by social scientists because, unlike other satellite-based data products, GRUMP urban extents include names and associated point locations, allowing for simpler cross-validation with administrative and survey data.

8 Tatem, Noor, and Hay (2005) compared five satellite-derived global urban maps including GRUMP to a medium-resolution settlement map of Kenya. Schneider, Friedl, and Potere (2009) compared the accuracy of six global urban maps including GRUMP against 140 medium-resolution city maps generated by Landsat imagery. Potere et al. (2009) compared eight global urban maps with 140 medium-resolution city maps and with 10,000 high-resolution Google Earth validation sites.

9 Fugate (2008) also used both remote-sensing data and DHS, but did not perform a cross-validation. She estimated the population size and population age structure of subnational regions by linking remote-sensing, census, and DHS data in one country, Egypt. Another study, by Doll and Pachauri (2010), examined the nighttime lights, GRUMP, and continental/regional–level data on access to electricity from the International Energy Agency. Their study examined rural areas broadly contrasted with urban areas only; their data on electricity are not spatial.

10 The spatial changes of urbanization may be happening so rapidly that the nightlights of 1995 substantially misrepresent the situation even ten years later. In our preliminary analysis, GRUMP's ability to capture highly electrified areas significantly declines after 2000, and is weaker than in the five-year interval around 1994–95. Other nighttime lights data may be used in the future to detect temporal changes (Kun et al. 2010); unlike the stable city-lights data used in GRUMP, these newer data sources detect only larger areas of dense electrification, and thus would need some analysis prior to becoming an urban application.

11 Readers familiar with DHS data know that clusters are not intended to be nationally representative. We describe a weighting scheme below to accommodate potential sampling concerns.

12 Functional definitions of urban also include populations engaged in nonagricultural activities; connectivity to infrastructure or other urban locations; or administrative centers.

13 That is, the *svyreg* function in Stata.

14 The example of Cameroon is merely illustrative; since we began this analysis, the DHS data producers have redacted the geocoded information for Cameroon 1998 as a result of irreversible errors (B. Zachary, personal communication).

15 We presented these findings to Measures DHS, and the Cameroon 1998 GPS files have been recalled. In our analysis, we use data from the 1991 Cameroon survey.

16 A more detailed list of DHS geocoding errors is available from the authors on request.

17 That is, the positional accuracy of the sensor responsible for the nightlights detection is accurate within 3 km. The true edge of the nightlights is somewhere between where it is rendered and up to an additional 3 km beyond. For this reason, DHS clusters located up to 3 km beyond the edge are considered to belong to the nearest light.

18 As noted above, our definition of improved sanitation is not limited to facilities connected to a sewer or septic tank.

19 We also performed a non-spatial cluster analysis to see how the different levels of access to services are grouped together and which groups were more likely to fall within GRUMP extents. The clusters with the highest levels of all services almost always fell within the GRUMP extents.

20 For calculation of overall map accuracy see Appendix Table A.2.

21 We do not imply that Google Maps can be used here in the same way other satellite-data sources are used, but it is an additional source of ad hoc cross-validation.

22 The exception was the cluster in Dubréka, Guinea, which appeared to be near a city. The coordinates for this cluster location are 9.7892N, 13.5188W.

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